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# Price Clustering, Preferences for Round Prices, and Expected Returns

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**ABSTRACT**
Researchers have documented that individuals have a strong penchant for round numbers in a variety of settings, such as trading in financial markets. Beginning as early as the 1930s, empirical research has shown that security prices tend to cluster on round increments. This anomalous finding has persisted over time and in a wide range of different types of securities markets. We examine whether stocks with greater price clustering experience excess demand and consequently, negative return premia. Using a variety of traditional asset pricing tests, we find support for this argument as price clustering is associated with a robust, negative return premium. Our results are robust to transaction-level clustering, cross-sectional regressions, and multi-factor models.

**KEYWORDS**
Price clustering; Expected returns; Behavioral economics; Behavioral finance; Round numbers

## Introduction

Research has shown that individuals have a strong penchant for round numbers. For instance, Pope and Simonsohn (2011) show that professional baseball players are almost four times as likely to end the season with a .300 batting average relative to a .299 average. The authors also show that students with SAT scores just below a round number are more likely to retake the exam than students with scores at a round number. The differences in behavior are explained, in part, by strong individual preferences for round numbers. These types of preferences are also evident in the financial economics literature. Gann (1930) was among the first to show that the most popular stock prices were those on round increments. Later, Wyckoff (1963) argued that because humans think in round numbers, they also trade in round numbers. Many other studies, in different asset markets, have documented evidence for the tendency of prices to cluster on round increments, which we denote, hereafter, as price clustering.[1]

The implications of price clustering are broad. The formation of equilibrium prices is a central tenet of microeconomic theory. Along these lines, Fama (1970) introduced the theory of efficient markets, which contends that prices that are determined in financial markets will reflect all available information. Observing that security prices are not uniformly distributed across all pricing increments questions the efficiency of financial markets generally. This propensity for security prices to cluster on round pricing increments is among the more persistent (across assets and across time) anomalies documented in the asset pricing literature.[2] While much of the prior literature has simply documented the presence of clustering, in this study, we seek to develop and test the idea that preferences for round numbers can have profound asset pricing implications. To the extent that traders have strong preferences for round prices, transactions may occur away from equilibrium values. Since market participants are net buyers in the long-run, transactions that occur at less precise clustered values may artificially inflate asset prices, resulting in subsequent underperformance.

In this study, we examine whether stocks that exhibit greater price clustering experience excess demand and consequently, exhibit negative return premia. The existing literature has provided the following explanations for investor preferences for round numbers. The first idea suggests that because investors think in round numbers, they prefer round prices to minimize cognitive processing costs (Wyckoff 1963; Niederhoffer and Osborne 1966). The second idea is motivated by the view of price resolution, which assumes that investors prefer round prices because they are unsure about the asset's true fundamental value (Ball, Torous, and Tschoegl 1985). The third

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idea suggests that traders prefer round numbers to minimize the costs associated with negotiations (Harris 1991). Regardless of which explanation has more merit, the preferences for round prices may have asset pricing implications.

To examine our research question, we gather pricing data from the Center for Research in Security Prices (CRSP) for 1980 to 2019. We then conduct a series of traditional asset pricing tests. We follow Harris (1991) and define price clustering as the percentage of days during a month that the share prices for a particular stock close on round increments. Our sample period covers two time periods over which the minimum allowable pricing increment (i.e., tick size) changed. Therefore, we partition our sample into two periods: the pre-decimalization period and the post-decimalization period. During the pre-decimalization period, when stocks traded on \$0.125 and \$0.0625, round prices are defined as increments of \$0.25. During the post-decimalization period, when stocks traded on \$0.01, round prices are defined as increments of \$0.05. Both our cross-sectional and portfolio tests indicate a significant negative return premium associated with price clustering.

In our initial tests, we estimate several Fama and MacBeth (1973) cross-sectional regressions that control for a variety of stock characteristics that have been shown to predict monthly returns, such as size, book-to-market ratios, momentum, illiquidity, and volatility. Results show that other factors held constant, price clustering predicts negative returns. In economic terms, a 1% increase in our measure of price clustering is associated with a reduction in next-month returns that ranges between 64 basis points (bps) and 85 bps depending on the econometric specification. These results are also robust to different functional forms of the control variables. Furthermore, we conduct our tests separately for the pre-decimalization and post-decimalization periods. We find that the negative return premium associated with price clustering is robust to both periods and, if anything, is slightly stronger during the post-decimalization era. We also note that the results are robust to the use of transaction-level data obtained from the NYSE Trade and Quote (TAQ) database for the period 2004 to 2019.

In our next tests, we conduct of series of portfolio sorts based on price clustering. We find that mean returns are decreasing across increasing price clustering portfolios that are formed during the previous month. While not monotonic, this negative association is both statistically significant and economically meaningful. For example, the difference between extreme portfolios is between 25 and 34 bps per month depending on how the portfolios are weighted. We also estimate a series of multi-factor models to determine whether alphas are also decreasing across increasing price clustering portfolios. We estimate a Fama and French (1996) and Carhart (1997) four-factor model, and we find that the alphas are also decreasing across increasing price clustering portfolios. Again, the differences between extreme portfolios range from 26 to 41 bps per month. In annual terms, our results indicate that stocks with the highest levels of price clustering underperform stocks with the lowest levels of price clustering between 3.12% and 5.04%. Our results are also robust to controls for a Pastor and Stambaugh (2003) liquidity risk factor.[3]

In our final tests, we examine whether the negative return premium associated with price clustering is demand-induced.[4] To do so, we partition the sample into quintiles in each month by the Carhart (1997) momentum factor. This allows us to identify stocks that experienced recent price appreciation (winners, or quintile 5) and those that experienced recent price depreciation (losers, or quintile 1). We then re-estimate the Fama and MacBeth (1973) cross-sectional tests separately for past winners and past losers. We find that the negative return premium associated with price clustering is entirely driven by past losers. Box and Griffith (2016) show that when stock market prices are falling, limit buy orders exhibit higher price clustering than limit sell orders, as clustered stop buy orders limit capital losses. Therefore, stocks that have performed poorly in the past are those that are expected to exhibit higher buy order clustering. Past losers must move through "demand-induced" pockets of clustered buy limit orders, which has the potential to buoy up their security prices and lead to future underperformance. Our results provide support for this conjecture.

Identifying a negative return premium associated with price clustering has important implications. First, we contribute to the understanding of price clustering by documenting that price clustering influences asset prices. Preferences for round prices appear to be strong enough to create demand-induced price premiums. Second, our results have important practical implications and suggest that alphas may exist in stocks with less price clustering. More broadly, our results have implications for the efficiency of financial markets. Niederhoffer (1966) contends that since prices are not distributed randomly across all pricing increments, price clustering may be inconsistent with efficient markets. At a minimum, price clustering seems to create return predictability that might also be inconsistent with strict forms of market efficiency.

The rest of the paper follows. The second section discusses the relevant literature. The third section describes the data used throughout the analysis. The fourth section reports the empirical methods and the results from our tests. The fifth section offers some concluding remarks.

## Related literature

First documented in Gann (1930) and formalized by Osborne (1962), price clustering, or the clustering of stock prices on round increments, has become a widely documented phenomenon in foreign exchange markets (Sopranzetti and Datar 2002), bond markets (Gwilym, Clare, and Thomas 1998a), futures and options markets (Gwilym and Alibo 2003; Gwilym, Clare, and Thomas 1998b; Ni, Pearson, and Poteshman 2005), and commodity markets (Ball, Torous, and Tschoegl 1985). The majority of the literature, however, has focused on price clustering in equity markets. Niederhoffer (1965), Niederhoffer (1966), and Niederhoffer and Osborne (1966) provide evidence that stock prices cluster on round increments. Other studies show that clustering is persistent in Asia-Pacific stock markets (Brown, Chua, and Mitchell 2002), including the Chinese and Hong Kong markets (Brown and Mitchell 2008; Ahn, Cai, and Cheung 2005), the Tokyo stock market (Ohta 2006), and the Dutch and Finnish stock markets (Sonnemans 2006; Booth, Kallunki, Lin, and Martikainen 2000). Perhaps the focus on clustering in equity markets is driven by the idea that stock prices are presumed to follow a random walk and, therefore, should be randomly distributed across all pricing increments. Thus, the presence of price clustering begins to question the efficiency of stock markets.

Wyckoff (1963) suggests that investors think in round numbers and, therefore, prefer round numbers to minimize cognitive processing costs. This explanation is sometimes referred to as the behavioral hypothesis for price clustering. Ball, Torous, and Tschoegl (1985) argue that investors trade in round numbers because they are uncertain about the assets' equilibrium values. This second explanation is described as the price resolution hypothesis. Harris (1991) argues that clustering is driven by investors' attempts to forego additional costs associated with further negotiations. This third explanation for the existence of price clustering is described as the negotiation hypothesis.

As mentioned above, the objective of this paper is not to determine why prices cluster on round increments, but instead, is to test whether or not price clustering influences asset prices. Our main hypothesis is that price clustering can create excess demand, which may lead to negative future returns. If the preferences for round prices are strong enough, and investors are net buyers in the long-run, clustering can create overvaluation and subsequent underperformance. Similar arguments have been made in the growing body of research that examines skewness, or lottery preferences. Kumar (2009), Boyer, Mitton, and Vorkink (2010), and Bali, Cakici, and Whitelaw (2011) suggest that preferences for stock characteristics that resemble lotteries, such as skewness, volatility, and days with unusually large returns, create price premiums. Similar arguments are made in Frazzini and Pedersen (2014), who argue that, when leverage constraints are binding, risk preferences can explain the negative return premium associated with high beta stocks. If indeed, the preferences for round numbers are strong enough to create excess demand or overvalued securities, then price clustering may be associated with a negative return premium.

## Data description

The data used throughout the analysis comes from two primary sources. From the Center for Research on Security Prices (CRSP), we obtain daily prices, returns, and volume and monthly prices, returns, and shares outstanding. From Compustat, we obtain annual balance sheet data for each security to estimate book-to-market ratios. When merging the CRSP and Compustat data, we require each stock to report a non-negative book-value of equity. Our sample period extends from 1980 to 2019. The final number of stock-month observations is nearly 2.3 million. Further, there are approximately 19,500 unique securities in the sample.

The variables used throughout the analysis are defined as follows. To obtain a measure of clustering, we follow Harris (1991) and count the number of days during each month that the share price for a particular stock closes on round increments of \$0.25 during the pre-decimalization period and \$0.05 during the post-decimalization period (*ClusterDays*). *Cluster%* is the percentage of days during the month that the closing price clusters on round increments. *Beta* is calculated as the slope coefficient from a Capital Asset Pricing Model (CAPM) using daily stock returns and daily estimates of the risk-free rate and the market

**Table 1.** Summary statistics.

| | Mean [1] | Median [2] | Standard Deviation [3] |
|---|---|---|---|
| *Panel A. Summary Statistics: Pre-Decimalization Period* | | | |
| ClusterDays | 10.3311 | 10.0000 | 5.2969 |
| Cluster% | 0.4906 | 0.5000 | 0.2499 |
| Beta | 0.5576 | 0.4732 | 2.7068 |
| Capitalization | 903,259,186 | 68,229,750 | 6,364,376,835 |
| B/M | 1.3567 | 0.6763 | 4.2488 |
| Momentum | 0.1628 | 0.1282 | 0.5665 |
| Illiquidity | 12.5225 | 0.2340 | 810.6367 |
| IdioVolt | 0.0303 | 0.0226 | 0.0289 |
| *Panel B. Summary Statistics: Post-Decimalization Period* | | | |
| ClusterDays | 6.5276 | 6.0000 | 3.7111 |
| Cluster% | 0.3118 | 0.2857 | 0.1767 |
| Beta | 0.9133 | 0.8714 | 1.1609 |
| Capitalization | 4,156,027,595 | 387,202,388 | 19,991,277,441 |
| B/M | 1.8534 | 0.6207 | 5.8012 |
| Momentum | 0.1213 | 0.1150 | 0.5240 |
| Illiquidity | 5.4588 | 0.0104 | 142.4324 |
| IdioVolt | 0.0237 | 0.0174 | 0.0233 |

The table provides summary statistics. Panel A presents the summary statistics for the variables used throughout the analysis during the pre-decimalization period (1980–2001) while Panel B provides the same statistics for the post-decimalization period (2001–2019). *ClusterDays* is the number of days during the month that the share prices for a particular stock close on a round increment of \$0.25 during the pre-decimalization period and \$0.05 during the post-decimalization period. *Cluster%* is the percent of days during the month that the prices for a particular stock close on these same round increments. *Beta* is calculated as the slope coefficient from a daily CAPM. *Capitalization* the market capitalization on the last day of each month (in \$billions). *B/M* is the book-to-market ratio. *Momentum* is the return from month $t-12$ to $t-2$. *Illiquidity* is the Amihud (2002) illiquidity measure, which is the monthly average of the ratio of the absolute value of the daily return scaled by the daily volume. *IdioVolt* is the idiosyncratic volatility. To obtain this measure of volatility, we first estimate a daily four-factor model (Fama and French 1996; Carhart 1997) and obtain daily residual returns. We then calculate *IdioVolt* as the standard deviation of these daily residual returns.

risk premium. We note that the risk-free rate and market risk premium are obtained from Wharton Research Data Services (WRDS). The risk-free rate is approximated by the 1-month yields on U.S. Treasury Bills, while the market return is the daily CRSP value-weighted return. *Capitalization* is the market capitalization on the last day of each month (in \$billions). *IdioVolt* is the idiosyncratic volatility. To obtain this measure of volatility, we first estimate a daily four-factor model (Fama and French 1996; Carhart 1997) and obtain daily residual returns for each stock in each month. Again, the daily risk factors (the market risk premium, *SMB*, *HML*, and *UMD*) are gathered from WRDS. We then calculate *IdioVolt* as the standard deviation of these daily residual returns. *B/M* is the book-to-market ratio and is obtained as the ratio of the annual book-value of equity on the balance sheet scaled by the monthly market capitalization. *Momentum* is the cumulative return from month $t-12$ to $t-2$. *Illiquidity* is the Amihud (2002) illiquidity measure, which is the monthly average of the ratio of the absolute value of the daily return scaled by the daily volume.

Table 1 reports statistics that describe our sample. Given that the pricing increments of stocks change during our sample period due to decimalization, we condition our tests on the pre-decimalization and post-decimalization period. Panel A reports the results for the pre-decimalization period while Panel B shows the summary statistics for the post-decimalization period. In the top panel, we find that, during the pre-decimalization period, the average stock has prices that close on round increments of 10.33 days per month (*ClusterDays* = 10.33), which equates to nearly 50% (*Cluster*%=0.4909) of possible days. Observing that approximately 50% of days close on a round increment of \$0.25 is expected given that there are only eight pricing increments. However, we note an important change that occurred during the pre-decimalization period. In 1997, the minimum tick size changed from 1/8th of a dollar to 1/16th of a dollar. Therefore, if closing prices are uniformly distributed across all pricing increments during the 1/8th environment, then the mean *Cluster*% should equal 50%. Alternatively, if the closing prices are uniformly distributed across all pricing increments during the 1/16th environment, then the mean *Cluster*% should equal 25%. In unreported tests, we find that the mean *Cluster*% is 52.16% from 1980 to 1996 and 39.10% from 1997 to 2000. These results suggest an unusual level of price clustering in both the 1/8th and 1/16th environments. We note that the mean of *Cluster*% (52.16%) is statistically different from 50% during the 1/8th environment while 39.10% is statistically different from 25% during the 1/16th environment. The rest of the summary statistics reported in Panel A show that the average stock in the pre-decimalization period has a *Beta* of .56, a *Capitalization* of \$.903 billion, a *B/M* ratio of 1.3567, *Momentum* of 16.28%, *Illiquidity* of 12.52, and *IdioVolt* is 3.03%.

Panel B shows that the average stock has share prices that cluster on round increments of \$0.05 nearly seven days per month. During the post-decimalization period, if closing prices are uniformly distributed across all pricing increments, then the mean *Cluster*% should equal 20%. Instead, Panel B shows that the mean and median of *Cluster*% is 31.18% and 28.57%, respectively. Again, statistical tests suggest that these percentages are reliably different from 20% suggesting that, consistent with prior research, prices have an unusual tendency to cluster on round pricing increments. During the post-decimalization period, the average stock has a *Beta* of .9133, a *Capitalization* of

**Table 2.** Fama and MacBeth (1973) regressions – The persistence of monthly clustering.

| | *Cluster%*$_{i,t}$ | | Ln(1+*ClusterDays*$_{i,t}$) | |
|---|---|---|---|---|
| | [1] | [2] | [3] | [4] |
| Cluster% | 0.5536*** | 0.4865*** | | |
| | (28.16) | (24.10) | | |
| Ln(1 + ClusterDays) | | | 0.5182*** | 0.4406*** |
| | | | (24.24) | (21.83) |
| Beta | | −0.0037*** | | −0.0092*** |
| | | (−9.08) | | (−6.77) |
| Capitalization | | 0.0007 | | 0.0047 |
| | | (0.79) | | (1.61) |
| B/M | | 0.0007 | | 0.0050*** |
| | | (1.52) | | (3.60) |
| Momentum | | 0.0116*** | | 0.0367*** |
| | | (15.32) | | (14.46) |
| Illiquidity | | −0.0001*** | | −0.0004*** |
| | | (−3.48) | | (−4.50) |
| IdioVolt | | −0.4616*** | | −1.5484*** |
| | | (−18.45) | | (−19.00) |
| Constant | 0.1570*** | 0.2002*** | 0.9492*** | 1.1198*** |
| | (42.17) | (11.13) | (27.77) | (13.87) |

The table presents the results from estimating the following equation using pooled stock-month data:

$$Cluster_{i,t} = \beta_1 Cluster_{i,t-1} + \beta_2 Beta_{i,t-1} + \beta_3 Ln\left(Capitalization_{i,t-1}\right) + \beta_4 Ln(B/M_{i,t-1}) + \beta_5 Momentum_{i,\{t-12,t-2\}} + \beta_6 Illiquidity_{i,t-1} + \beta_7 Idiovolt_{i,t-1} + \alpha + \varepsilon_{i,t},$$

where the dependent variable is one of two measures of clustering, Ln(1+*ClusterDays*) or *Cluster%*. Ln(1+*ClusterDays*) is the natural log of one plus the number of days during the month that the share prices for a particular stock close on a round increment of \$0.25 during the pre-decimalization period and \$0.05 during the post-decimalization period. *Cluster%* is the percent of days during the month that the prices for a particular stock close on these same round increments. *Beta* is calculated as the slope coefficient from a daily CAPM. *Capitalization* the market capitalization on the last day of each month (in \$billions). *B/M* is the book-to-market ratio. *Momentum* is the return from month $t-12$ to $t-2$. *Illiquidity* is the Amihud (2002) illiquidity measure, which is the monthly average of the ratio of the absolute value of the daily return scaled by the daily volume. *IdioVolt* is the idiosyncratic volatility. To obtain this measure of volatility, we first estimate a daily four-factor model (Fama and French 1996; Carhart 1997) and obtain daily residual returns. We then calculate *IdioVolt* as the standard deviation of these daily residual returns. We estimate the equation using a Fama and MacBeth (1973) approach. In parentheses, we report *t*-statistics that are obtained from Newey and West (1987) standard errors that account for three lags. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

\$4.156 billion, a *B/M* ratio of 1.8534, *Momentum* of 12.13%, *Illiquidity* of 5.4588, and *IdioVolt* of 2.37%.

## Empirical results

In this section of the paper, we describe the methods for and results from our empirical tests. We begin by first providing some tests of the persistence of price clustering through time. We then conduct of series of cross-sectional tests using Fama and MacBeth (1973) regressions. In our final set of tests, we sort stocks into portfolios based on the level of price clustering and estimate multi-factor models to determine whether alphas exist in various price clustering portfolios.

### *The persistence of price clustering*

Before conducting our asset pricing tests, we first seek to determine whether price clustering is persistent from month to month. To do so, we follow the methods of Bali, Cakici, and Whitelaw (2011) who attempt to show that the maximum daily returns are persistent in the cross section. In particular, we estimate the following equation using pooled stock-month data.

$$Cluster_{i,t} = \beta_1 Cluster_{i,t-1} + \beta_2 Beta_{i,t-1} + \beta_3 Ln\left(Capitalization_{i,t-1}\right) + \beta_4 Ln(B/M_{i,t-1}) + \beta_5 Momentum_{i,\{t-12,t-2\}} + \beta_6 Illiquidity_{i,t-1} + \beta_7 Idiovolt_{i,t-1} + \alpha + \varepsilon_{i,t} \tag{1}$$

The dependent variable is one of two measures of clustering, *Cluster%* or Ln(1+*ClusterDays*), which have previously been defined. We note that we add one to *ClusterDays* to ensure that the natural log is defined. We include, as the variable of interest, the lagged (i.e. $t-1$) dependent variable along with several other control variables, which were defined in the previous section. We estimate the equation using a Fama and MacBeth (1973) approach. In parentheses, we report *t*-statistics that are obtained from Newey and West (1987) standard errors that account for three lags.

Table 2 reports the results from estimating Equation 1. Columns [1] and [3] show the results for

**Table 3.** Fama and MacBeth (1973) regressions – price clustering and expected returns.

| | [1] | [2] | [3] | [4] | [5] | [6] | [7] |
|---|---|---|---|---|---|---|---|
| Cluster% | −0.0068** | −0.0069** | −0.0064** | −0.0079*** | −0.0085*** | −0.0077*** | −0.0074*** |
| | (−2.37) | (−2.50) | (−2.29) | (−2.79) | (−3.21) | (−2.91) | (−3.15) |
| Beta | | −0.0007 | −0.0002 | 0.0000 | −0.0003 | −0.0002 | 0.0000 |
| | | (−1.04) | (−0.26) | (0.05) | (−0.50) | (−0.37) | (0.01) |
| Capitalization | | | −0.0016*** | −0.0009** | −0.0010** | −0.0008* | −0.0009*** |
| | | | (−3.69) | (−2.07) | (−2.31) | (−1.89) | (−2.62) |
| B/M | | | | 0.0061*** | 0.0064*** | 0.0063*** | 0.0062*** |
| | | | | (8.84) | (10.58) | (10.65) | (11.51) |
| Momentum | | | – | | 0.0050*** | 0.0055*** | 0.0055*** |
| | | | | | (3.82) | (4.00) | (4.28) |
| Illiquidity | | | | | | 0.0001*** | 0.0001*** |
| | | | | | | (4.16) | (4.57) |
| IdioVolt | | | | | | | −0.0678** |
| | | | | | | | (−2.05) |
| Constant | 0.0148*** | 0.0153*** | 0.0437*** | 0.0347*** | 0.0354*** | 0.0312*** | 0.0335*** |
| | (4.12) | (4.52) | (4.09) | (3.16) | (3.36) | (2.96) | (4.11) |

The table reports the Fama and MacBeth (1973) regression results from estimating variants of the following equation using pooled stock-month data:

$$R_{i,t} = \beta_1 Cluster\%_{i,t-1} + \beta_2 Beta_{i,t-1} + \beta_3 Ln\left(Capitalization_{i,t-1}\right) + \beta_4 Ln(B/M_{i,t-1}) + \beta_5 Momentum_{i,\{t-12,t-2\}} + \beta_6 Illiquidity_{i,t-1} + \beta_7 Idiovolt_{i,t-1} + \alpha + \varepsilon_{i,t},$$

where the dependent variable is the return for stock *i* in month *t*. The independent variable of interest is *Cluster%*, which is the percent of days during the month that the prices for a particular stock close on round increments of $0.25 during the pre-decimalization period and $0.05 during the post-decimalization period. *Beta* is calculated as the slope coefficient from a daily CAPM. *Capitalization* the market capitalization on the last day of each month (in $billions). *B/M* is the book-to-market ratio. *Momentum* is the return from month $t-12$ to $t-2$. *Illiquidity* is the Amihud (2002) illiquidity measure, which is the monthly average of the ratio of the absolute value of the daily return scaled by the daily volume. *IdioVolt* is the idiosyncratic volatility. To obtain this measure of volatility, we first estimate a daily four-factor model (Fama and French 1996; Carhart 1997) and obtain daily residual returns. We then calculate *IdioVolt* as the standard deviation of these daily residual returns. In parentheses, we report *t*-statistics that are obtained from standard errors with the Newey and West (1987) adjustments that include three lags. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

simple specifications that only include the lagged dependent variables as regressors, while columns [2] and [4] provide results from the full model specifications. Column [1] shows that the estimate for the lagged dependent variable is .5536 (*t*-statistic = 28.16), suggesting that *Cluster%* in a particular month is a good predictor of *Cluster%* in the following month. Of course, an estimate of one would mean that *Cluster%* is perfectly persistent. Column [2] shows that, after controlling for several lagged stock characteristics, *Cluster%* is still relatively persistent (estimate=.4865, *t*-statistic = 24.10). We also note that each of the control variables produces a reliable estimate, except for *Capitalization* and *B/M*, which are not significant at the 0.10 level. For instance, *Momentum* is a positive predictor of *Cluster%* while *Beta*, *Illiquidity*, and *IdioVolt* are negative predictors of *Cluster%*. The results in columns [3] and [4] where the cluster variable is the Ln(1+*ClusterDays*) are seemingly identical (estimates=.5182, .4406; *t*-statistics = 24.24, 21.83) to those found in the first two columns. These results highlight the importance of controlling for these stock characteristics in the asset pricing tests below.

### *Price clustering and asset prices – cross-sectional tests*

In this subsection and the one that follows, we begin our tests of the return premium associated with price clustering. Here, we use Fama and MacBeth (1973) regressions to test for the cross-sectional return premium associated with price clustering. In particular, we estimate the following equation using pooled stock-month observations:

$$R_{i,t} = \beta_1 Cluster_{i,t-1} + \beta_2 Beta_{i,t-1} + \beta_3 Ln\left(Capitalization_{i,t-1}\right) + \beta_4 Ln(B/M_{i,t-1}) + \beta_5 Momentum_{i,\{t-12,t-2\}} + \beta_6 Illiquidity_{i,t-1} + \beta_7 Idiovolt_{i,t-1} + \alpha + \varepsilon_{i,t} \quad (2)$$

where the dependent variable is the monthly return for stock *i* in month *t*. The independent variable of interest is either *Cluster%* or *ClusterDays*. The remaining independent variables have previously been defined. We note that, other than *Momentum*, all of the independent variables are measured in month $t-1$. In parentheses, we report *t*-statistics that are obtained from standard errors with the Newey and West (1987) adjustments that include three lags.

Table 3 reports the results from estimating Equation 2 where the independent variable of interest is set to *Cluster%*. To show robustness in our results, we estimate variants of Equation 2 by including different combinations of independent variables in columns [1] through [7]. Column [8] provides the results from

**Table 4.** Fama and MacBeth (1973) regressions – price clustering and expected returns.

| | [1] | [2] | [3] | [4] | [5] | [6] | [7] |
|---|---|---|---|---|---|---|---|
| Ln(1 + ClusterDays) | −0.0034*** | −0.0034*** | −0.0030*** | −0.0037*** | −0.0039*** | −0.0034*** | −0.0033*** |
| | (−2.99) | (−3.12) | (−2.90) | (−3.57) | (−4.07) | (−3.58) | (−3.85) |
| Beta | | −0.0006 | −0.0002 | 0.0000 | −0.0003 | −0.0002 | 0.0000 |
| | | (−0.98) | (−0.25) | (0.08) | (−0.47) | (−0.33) | (0.04) |
| Capitalization | | | −0.0015*** | −0.0008* | −0.0009** | −0.0007 | −0.0008** |
| | | | (−3.57) | (−1 − 80) | (−2.03) | (−1.63) | (−2.30) |
| B/M | | | | 0.0062*** | 0.0065*** | 0.0064*** | 0.0063*** |
| | | | | (8.90) | (10.65) | (10.72) | (11.58) |
| Momentum | | | | | 0.0051*** | 0.0055*** | 0.0056*** |
| | | | | | (3.85) | (4.03) | (4.31) |
| Illiquidity | | | | | | 0.0001*** | 0.0001*** |
| | | | | | | (4.16) | (4.56) |
| IdioVolt | | | | | | | −0.0677** |
| | | | | | | | (−2.04) |
| Constant | 0.0194*** | 0.0199*** | 0.0460*** | 0.0370*** | 0.0379*** | 0.0332*** | 0.0353*** |
| | (4.25) | (4.61) | (4.08) | (3.19) | (3.41) | (2.99) | (4.15) |

The table reports the Fama and MacBeth (1973) regression results from estimating variants of the following equation using pooled stock-month data.

$$R_{i,t} = \beta_1 Ln(1 + ClusterDays_{i,t-1}) + \beta_2 Beta_{i,t-1} + \beta_3 Ln\left(Capitalization_{i,t-1}\right) + \beta_4 Ln(B/M_{i,t-1})$$
$$+ \beta_5 Momentum_{i,\{t-12,t-2\}} + \beta_6 Illiquidity_{i,t-1} + \beta_7 Idiovolt_{i,t-1} + \alpha + \varepsilon_{i,t},$$

where the dependent variable is the return for stock *i* in month *t*. The independent variable of interest is Ln(1+*ClusterDays*), which is the natural log of one plus the number of days during a particular month that stock prices close on a round increment of $0.25 during the pre-decimalization period or $0.05 during the post-decimalization period. *Beta* is calculated as the slope coefficient from a daily CAPM. *Capitalization* the market capitalization on the last day of each month (in $billions). *B/M* is the book-to-market ratio. *Momentum* is the return from month $t-12$ to $t-2$. *Illiquidity* is the Amihud (2002) illiquidity measure, which is the monthly average of the ratio of the absolute value of the daily return scaled by the daily volume. *IdioVolt* is the idiosyncratic volatility. To obtain this measure of volatility, we first estimate a daily four-factor model (Fama and French 1996; Carhart 1997) and obtain daily residual returns. We then calculate *IdioVolt* as the standard deviation of these daily residual returns. In parentheses, we report *t*-statistics that are obtained from standard errors with the Newey and West (1987) adjustments that include three lags. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

the full model specification. A few general results about the control variables are noteworthy. First, we find consistency with a broad range of literature including Banz (1981) and Fama and French 1992) as *Capitalization* is negatively associated with future returns. We also find a value premium (Fama and French 1992) as the *B/M* produces positive and statistically significant estimates. Consistent with Jegadeesh and Titman (1993), we find a positive return premium associated with *Momentum*. Furthermore, we find that *Illiquidity* also predicts positive returns, which is similar to the findings in Amihud and Mendleson (1986) and Amihud (2002), among others. Lastly, we find some evidence that the estimate for *IdioVolt* is negative, which is consistent with the findings in Ang et al. (2006, 2009).

We now turn our focus to the independent variable of interest, *Cluster%*. The simple regression in column [1] shows that *Cluster%* produces a negative estimate that is both statistically significant and economically meaningful. For instance, a one percent increase in *Cluster%* is associated with a reduction in next-month returns of nearly 68 bps. Similar results are found in columns [2] through [7] as we include different control variables. In these six columns, the negative return premium associated with price clustering ranges from 64 to 85 bps per month. In each of the seven columns, the coefficient on price clustering is at least statistically significant at the .05 level. In the full model specification in column [7], we still observe a reliable, negative coefficient on *Cluster%* (estimate= −.0074, *t*-statistic= −3.15). These results again suggest that, after controlling for several factors that have been shown to influence future returns, price clustering is an important, cross-sectional predictor of negative returns. Perhaps what is more interesting is the magnitude of the price clustering premium. Column [7] indicates that a one percent increase in *Cluster%* is associated with a 74-bp reduction in next-month returns, other risk factors held constant.

Next, we continue our analysis by estimating Equation 2, but inserting Ln(1+*ClusterDays*) as the independent variable of interest. Table 4 provides the results from this analysis. For brevity, we focus primarily on our independent variable of interest but note that the coefficients on the control variables are similar to the corresponding coefficients in the previous table. In each of the eight columns, we find that the coefficient on Ln(1+*ClusterDays*) is reliably different from zero at the .01 level. In economic terms, the coefficient in column [1] suggests that a one percent increase in the number of days that share prices close on round increments is associated with a 34-bp reduction in next-month returns. Qualitatively similar results are found in each of the specifications. In the full model specification in column [7], we find that

**Table 5.** Fama and MacBeth (1973) regressions – the pre- and post-decimalization periods.

| | Pre-Decimalization Period | | Post-Decimalization Period | |
|---|---|---|---|---|
| | [1] | [2] | [3] | [4] |
| Cluster% | −0.0061** | | −0.0088** | |
| | (−2.03) | | (−2.33) | |
| Ln(1 + ClusterDays) | | −0.0034*** | | −0.0032** |
| | | (−2.77) | | (−2.55) |
| Beta | 0.0001 | 0.0001 | −0.0001 | −0.0000 |
| | (0.13) | (0.14) | (−0.07) | (−0.04) |
| Capitalization | −0.0008 | −0.0006 | −0.0010** | −0.0010** |
| | (−1.41) | (−1.03) | (−2.33) | (−2.32) |
| B/M | 0.0082*** | 0.0083*** | 0.0040*** | 0.0040*** |
| | (10.14) | (10.29) | (7.05) | (7.05) |
| Momentum | 0.0092*** | 0.0092*** | 0.0015 | 0.0015 |
| | (6.58) | (6.63) | (0.70) | (0.71) |
| Illiquidity | 0.0001*** | 0.0001*** | 0.0001** | 0.0001** |
| | (4.21) | (4.22) | (2.57) | (2.56) |
| IdioVolt | −0.0569 | −0.0565 | −0.0798* | −0.0800* |
| | (−1.21) | (−1.20) | (−1.67) | (−1.67) |
| Constant | 0.0325*** | 0.0332*** | 0.0347*** | 0.0376*** |
| | (2.63) | (2.60) | (3.05) | (3.12) |

The table reports the Fama and MacBeth (1973) regression results from estimating variants of the following equation using pooled stock-month data in the pre-decimalization period (1980–2001) and post-decimalization period (2002–2019) separately:

$$R_(i,t) = \beta_1 \ 〚Cluster〛_(\mathrm{i,t-1}) + \beta_2 \ 〚Beta〛_(\mathrm{i,t-1}) + \beta_3 \ \mathrm{Ln}(〚Capitalization〛_(\mathrm{i,t-1})) + \beta_4 \ \mathrm{Ln}(〚\mathrm{B/M}〛_(\mathrm{i,t-1})) + \beta_5 \ 〚Momentum〛_(\mathrm{i},\{\mathrm{t}-12,\mathrm{t}-2\}) + \beta_6 \ 〚Illiquidity〛_(\mathrm{i,t-1}) + \beta_7 \ 〚Idiovolt〛_(\mathrm{i,t-1}) + \alpha + \varepsilon_(\mathrm{i,t}),$$

where the dependent variable is the return for stock *i* in month *t*. The independent variable of interest is one of two measures of clustering, Ln(1 + ClusterDays) or Cluster%. Ln(1 + ClusterDays) is the natural log of one plus the number of days during the month that the share prices for a particular stock close on a round increment of \$0.25 during the pre-decimalization period and \$0.05 during the post-decimalization period. Cluster% is the percent of days during the month that the prices for a particular stock close on these same round increments. Beta is calculated as the slope coefficient from a daily CAPM. Capitalization the market capitalization on the last day of each month (in \$billions). B/M is the book-to-market ratio. Momentum is the return from month $t-12$ to $t-2$. Illiquidity is the Amihud (2002) illiquidity measure, which is the monthly average of the ratio of the absolute value of the daily return scaled by the daily volume. IdioVolt is the idiosyncratic volatility. To obtain this measure of volatility, we first estimate a daily four-factor model (Fama and French 1996; Carhart 1997) and obtain daily residual returns. We then calculate IdioVolt as the standard deviation of these daily residual returns. In parentheses, we report *t*-statistics that are obtained from standard errors with the Newey and West (1987) adjustments that include three lags. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

the estimate on Ln(1+*ClusterDays*) is −.0033 (*t*-statistic= −3.85) suggesting that a one percent increase in *ClusterDays* is associated with a 30-bp reduction in next-month returns. Consistent with findings from Table 3, the results in Table 4 identifies a large and robust, negative return premium associated with price clustering. These findings tend to support our hypothesis. Stated differently, the negative, price clustering return premium seems to indicate that individual preferences for round prices are strong enough to influence asset prices. In particular, these preferences seem to create excess demand and lead to price premiums and subsequent underperformance.

## *Price clustering and asset prices – pre-decimalization versus post-decimalization periods*

Next, we provide some robustness to our tests in Tables 3 and 4. As mentioned above, our definition of price clustering changes during our sample period since the minimum tick size for which stocks could trade changes. This important shift requires us to test whether the return premium associated with price clustering was driven completely by the pre-decimalization period and is no longer relevant for the post-decimalization period. We re-estimate Equation 2 separately for the pre-decimalization and post-decimalization periods. The results of this analysis are found in Table 5. For brevity, we only report our full specifications, although qualitatively similar results are found when we include different combinations of control variables.

Column [1] shows the results for the pre-decimalization period when *Cluster*% is the independent variable of interest. In general, the control variables produce estimates that are similar in sign and magnitude to the corresponding coefficients in Table 3. We note that the estimates for *Capitalization* and *IdioVolt* are no longer significant in column [1]. More importantly, we find that the *Cluster*% produces a negative and reliable estimate (estimate= −.0061, *t*-statistic= −2.03). In economic terms, a one percent increase in *Cluster*% is associated with a 61-bp reduction in next-month returns. Similar results are found in column [2] where

Ln(1+*ClusterDays*) is included as the independent variable of interest. In particular, the coefficient on Ln(1+*ClusterDays*) is −.0034 (*t*-statistics= −2.77) and suggests that a one percent increase in the number of days that cluster on round pricing increments is associated with an approximate 34-bp reduction in next-month returns.

Columns [3] and [4] provide the results for the post-decimalization period. Again, the control variables produce similar results to those in previous columns and tables with one exception. We no longer find a reliable *Momentum* return premium during the post-decimalization period. Column [3] shows that *Cluster*% produces a negative estimate that is both statistically and economically impactful (estimate= −.0088, *t*-statistic= −2.33). For instance, a 1% increase in *Cluster*% is associated with an 88-bp reduction in next-month returns. Compared to the results in column [1], we find that the return premium associated with *Cluster*% increases (in absolute value) during the latter sample period. Column [4] shows the results when Ln(1+*ClusterDays*) is included instead of *Cluster*%. Again, we find that the estimate on Ln(1+*ClusterDays*) is relatively constant across the different time periods (estimate= −.0032, *t*-statistic= −2.55). In economic terms, a one percent increase in the number of days that share prices close on round pricing increments is associated with a 32 bp reduction in next-month returns. The findings in Table 5 seem to indicate that the price clustering return premium is not an artifact of the pre-decimalization period and, if anything, the return premium is, at least as strong during the post-decimalization period.

## Price clustering and asset prices – transaction-level price clustering

To provide further robustness for our main cross-sectional regression results, we gather intraday transaction-level data from the NYSE Trade and Quote (TAQ) database from 2004 to 2019.[5] We then estimate price clustering as the percent of transactions on a particular stock-day that execute on increments of $0.05 (*TCluster*%). We also estimate price clustering using trading volumes. In particular, we sum the share volume on a particular stock-day that executes on round transaction prices and divide it by the total share volume for the same stock-day (*VCluster*%). We then average these stock-day clustering measures to the stock-month level. In unreported tests, we show that these high-frequency measures of clustering obtained from TAQ (*TCluster*% and *VCluster*%) and the low-frequency proxies of clustering obtained from CRSP (*Cluster*% and *ClusterDays*) have cross-sectional correlation coefficients that are roughly 0.90. To test the validity of the results reported in the previous subsections, we re-estimate Equation 2 but replace the *Cluster* independent variable with either *TCluster*% or *VCluster*%. The results of this analysis are reported in Table 6.

The control variables in Table 6 produce their expected signs. Therefore, we focus our discussion on the price clustering variables on interest. In column [1], we find that the estimated coefficient on *TCluster*% is negative and significant at the 0.05 level. In economic terms, a one percent increase in *TCluster*% is associated with a 219-bp decrease in next-month's return, other factors held constant. Similarly, in column [2], we report that the estimated coefficient on *VCluster*% is negative and statistically different from zero. The results suggest that a one percent increase in transaction volume clustering is associated with a 158-bp decrease in next-month's return – ceteris paribus. The results in this subsection indicate that our results are robust to the use of transaction prices and transaction volumes, and give us confidence in our low-frequency CRSP proxies.

## Price clustering and asset prices – univariate portfolio tests

In this subsection, we examine the return premium associated with price clustering using a portfolio approach. In particular, each month, we sort stocks into five portfolios based on the level of last month's price clustering and examine the current month's returns using a series of univariate and multi-variate factor models. The objective is to determine whether returns decrease across increasing portfolios sorted on price clustering. We note that in this subsection, we do not sort stocks based on *ClusterDays* given that doing so would simply reproduce the portfolios sorted on *Cluster*%. We begin by conducting some univariate tests by examining mean returns across portfolios sorted on last month's price clustering. Table 7 reports these results for portfolios that are equally weighted (panel A) and value-weighted (panel B). In the table, we report the mean raw return and adjusted return, which is calculated as the difference between raw returns and market returns.

Panel A of Table 7 shows the mean returns from equally weighted portfolios. As seen in the first row of the table, returns are generally decreasing across increasing portfolios. In column [6], we report the

**Table 6.** Fama and MacBeth (1973) regressions – transaction-level clustering.

| | Cluster=*TCluster%* [1] | Cluster=*VCluster%* [2] |
|---|---|---|
| Cluster | −0.0219** | −0.0158** |
| | (−2.56) | (−2.16) |
| Beta | −0.0006 | −0.0006 |
| | (−0.58) | (−0.53) |
| Capitalization | −0.0014*** | −0.0013*** |
| | (−3.04) | (−2.93) |
| B/M | 0.0019*** | 0.0019*** |
| | (3.78) | (3.80) |
| Momentum | −0.0026 | −0.0027 |
| | (−1.06) | (−1.09) |
| Illiquidity | 0.0001*** | 0.0001*** |
| | (3.10) | (2.98) |
| Idiovolt | 0.0021 | 0.0072 |
| | (0.04) | (0.15) |
| Constant | 0.0435*** | 0.0403*** |
| | (3.43) | (3.30) |

The table reports the Fama and MacBeth (1973) regression results from estimating variants of the following equation using pooled stock-month data obtained from intraday NYSE Trade and Quote (TAQ) files for 2004 to 2019:

$$R_(i,t) = \beta_1 \ 〚Cluster〛_(\mathrm{i,t}-1) + \beta_2 \ 〚Beta〛_(\mathrm{i,t}-1) + \beta_3 \ \mathrm{Ln}(〚Capitalization〛_(\mathrm{i,t}-1)) + \beta_4 \ \mathrm{Ln}(〚\mathrm{B/M}〛_(\mathrm{i,t}-1)) + \beta_5 \ 〚Momentum〛_(\mathrm{i},\{\mathrm{t}-12,\mathrm{t}-2\}) + \beta_6 \ 〚Illiquidity〛_(\mathrm{i,t}-1) + \beta_7 \ 〚Idiovolt〛_(\mathrm{i,t}-1) + \alpha + \varepsilon_(\mathrm{i,t}),$$

where the dependent variable is the return for stock *i* in month *t*. The independent variable of interest is one of two measures of clustering, TCluster% or VCluster%. TCluster% is the percentage of transaction prices that cluster on increments of \$0.05 during a trading session. VCluster% is the percentage of share volume during the trading day that executes on increments of \$0.05 to total share volume traded. We estimate these TAQ measures on a stock-day basis and then average across stock-months. Beta is calculated as the slope coefficient from a daily CAPM. Capitalization the market capitalization on the last day of each month (in \$billions). B/M is the book-to-market ratio. Momentum is the return from month $t-12$ to $t-2$. Illiquidity is the Amihud (2002) illiquidity measure, which is the monthly average of the ratio of the absolute value of the daily return scaled by the daily volume. IdioVolt is the idiosyncratic volatility. To obtain this measure of volatility, we first estimate a daily four-factor model (Fama and French 1996; Carhart 1997) and obtain daily residual returns. We then calculate IdioVolt as the standard deviation of these daily residual returns. In parentheses, we report *t*-statistics that are obtained from standard errors with the Newey and West (1987) adjustments that include three lags. ** and *** denote statistical significance at the 0.05 and 0.01 levels, respectively.

**Table 7.** Portfolio analysis – univariate sorts.

| | Q1 (Low) [1] | Q2 [2] | Q3 [3] | Q4 [4] | Q5 (High) [5] | Q5 – Q1 [6] |
|---|---|---|---|---|---|---|
| *Panel A. Mean Returns across Cluster% Equal-Weighted Portfolios* | | | | | | |
| Mean Returns | 0.0146 | 0.0115 | 0.0113 | 0.0114 | 0.0111 | −0.0034** |
| | | | | | | (−2.37) |
| Adj. Returns | 0.0026 | −0.0005 | −0.0007 | −0.0005 | −0.0008 | −0.0034** |
| | | | | | | (−2.37) |
| *Panel B. Mean Returns across Cluster% Value-Weighted Portfolios* | | | | | | |
| Mean Returns | 0.0203 | 0.0164 | 0.0157 | 0.0167 | 0.0178 | −0.0025* |
| | | | | | | (−1.78) |
| Adj. Returns | 0.0038 | −0.0001 | −0.0008 | 0.0002 | 0.0013 | −0.0025* |
| | | | | | | (−1.78) |

The table report mean returns across portfolios sorted by Cluster%, which is the percent of days during the month that the prices for a particular stock close on round increments of \$0.25 during the pre-decimalization period and \$0.05 during the post-decimalization period. Both panels present the Mean Raw Returns and Adj. Returns, which are returns in month t in excess of the market index. Panel A consists of portfolios that are equal-weighted and formed in month $t-1$. Panel B consists of portfolios that are value-weighted and formed in month $t-1$. Column [6] reports the difference between extreme Cluster% portfolios along with corresponding *t*-statistics in parentheses. The table reports the results using 479 months of data by portfolios based on Cluster%. * and ** denote statistical significance at the 0.10 and 0.05 levels, respectively.

differences in mean returns between extreme portfolios. In the first row, we find that the high-minus-low difference is −.0034, which is statistically significant (*t*-statistic= −2.37). These results indicate that, according to our portfolio analysis, the return premium associated with price clustering is 34 bps per month. Qualitatively similar results are found in the second row of panel A, which focuses on adjusted returns.

Panel B of Table 7 shows the results when we evaluate mean returns from value-weighted portfolios. We again find that, in general, raw returns (and adjusted returns) are decreasing across increasing portfolios. Column [6] reports that high-minus-low differences are marginally significant. In economic terms, the return premium associated with price clustering is 25 bps per month.

**Table 8.** Portfolio analysis – four-factor regression analysis.

| | Q1 (Low) [1] | Q2 [2] | Q3 [3] | Q4 [4] | Q5 (High) [5] | Q5 – Q1 [6] |
|---|---|---|---|---|---|---|
| *Panel A. 4-Factor Regressions by Equal-Weighted Cluster% Portfolios* | | | | | | |
| ALPHA | 0.0023*** | −0.0005** | −0.0008** | −0.0005 | −0.0003 | −0.0026** |
| | (2.71) | (−1.96) | (−2.29) | (−1.35) | (−0.48) | (−2.00) |
| MRP | 1.0977*** | 1.0414*** | 1.0116*** | 0.9747*** | 0.8646*** | −0.2331*** |
| | (48.88) | (151.12) | (122.79) | (106.50) | (62.18) | (−6.87) |
| SMB | 0.0419 | −0.0349** | −0.0320** | −0.0143 | 0.0387 | −0.0032 |
| | (0.98) | (−2.24) | (−2.28) | (−0.72) | (1.47) | (−0.05) |
| HML | −0.0090 | −0.0078 | 0.0044 | 0.0028 | 0.0199 | 0.0289 |
| | (−0.24) | (−0.67) | (0.27) | (0.17) | (0.80) | (0.50) |
| UMD | −0.0945*** | −0.0443*** | 0.0054 | 0.0392** | 0.0939*** | 0.1883*** |
| | (−2.68) | (−6.02) | (0.44) | (2.04) | (4.99) | (3.60) |
| *Panel B. 4-Factor Regressions by Value-Weighted Cluster% Portfolios* | | | | | | |
| ALPHA | 0.0047*** | 0.0004 | −0.0009** | −0.0005 | 0.0006 | −0.0041*** |
| | (4.33) | (0.77) | (−1.98) | (−0.98) | (0.78) | (−2.87) |
| MRP | 0.9714*** | 0.9739*** | 0.9977*** | 1.0325*** | 1.0299*** | 0.0585 |
| | (31.98) | (82.50) | (74.34) | (74.08) | (48.52) | (1.46) |
| SMB | 0.1022* | −0.0023 | −0.0154 | −0.0396* | 0.1703*** | 0.0680 |
| | (1.88) | (−0.10) | (−0.96) | (−1.79) | (4.65) | (0.90) |
| HML | 0.0056 | 0.0095 | 0.0602*** | −0.0093 | −0.0522 | −0.0578 |
| | (0.16) | (0.47) | (3.64) | (−0.49) | (−1.25) | (−0.90) |
| UMD | −0.1034*** | −0.0251 | 0.0042 | 0.0536*** | 0.0594** | 0.1627*** |
| | (−3.27) | (−1.34) | (0.33) | (3.56) | (2.21) | (3.31) |

The table reports alphas from estimating the following equation using 479 months of data by portfolios based on Cluster%, which is the percent of days during the month that the prices for a particular stock close on round increments of \$0.25 during the pre-decimalization period and \$0.05 during the post-decimalization period:

$$R_t - R(f,t) = \alpha + \beta_1 〖MRP〗_t + \beta_2 〖HML〗_t + \beta_3 〖SMB〗_t + \beta_4 〖UMD〗_t + \varepsilon_t,$$

where the dependent variable is the excess return of the portfolio over the 1-month T-Bill yield. The independent variables include the following variables. MRP is the market risk premium or the return of the market less the risk-free rate. SMB is the small-minus-big risk factor. HML is the high-minus-low risk factor. UMD is the up-minus-down momentum risk factor. While the variables are measured over month *t*, the portfolios are sorted at the end of month $t-1$. Robust (White 1980) *t*-statistics are reported in parentheses. Panel A consists of equal-weighted portfolios sorted in month $t-1$. Panel B consists of portfolios that are value-weighted sorted in month $t-1$. Column [6] reports the difference between extreme portfolios. *, **, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Next, we implement traditional multi-factor models to estimate alphas. In particular, we estimate variants of the following equation for each of the five price clustering portfolios:

$$R_t - R_{f,t} = \alpha + \beta_1 MRP_t + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 UMD_t + \varepsilon_t, \quad (3)$$

where the dependent variable is the excess return of the portfolio over the 1-month U.S. T-Bill yield. The independent variables include the following: *MRP* is the market risk premium or the expected return of the market less the risk-free rate. *SMB* is the small-minus-big return factor. *HML* is the high-minus-low return factor. *UMD* is the up-minus-down momentum factor. The dependent and independent variables are measured over month *t* while the portfolios are sorted at the end of month $t-1$. We use robust (White 1980) standard errors in the estimation of *t*-statistics.

Table 8 presents the results from the multi-factor analysis. Like in the previous table, panel A reports the results for analysis for equal-weighted portfolios, while panel B shows the results for the value-weighted portfolios. Panel A of Table 8 shows that the alphas from the Fama and French (1996) and Carhart (1997) four-factor model are generally decreasing across increasing portfolios. Column [1] shows that stocks with the lowest levels of price clustering have four-factor alphas of 23 bps per month. In annual terms, this alpha represents more than 2.8% in expected returns. We estimate Equation 4 using the return differences between extreme portfolios as the dependent variable in column [6]. Here, the estimated alpha in column [6] is .26% per month (*t*-statistic$=-2.00$), which reflects more than 3% in annual terms. These results support the findings from previous panels and indicate that the return premium associated with price clustering is both statistically and economically significant.

Panel B of Table 8 shows the results when we analyze value-weighted portfolios. Again, we find that stocks with the lowest level of price clustering exhibit a positive return premium as the estimated alpha is .0047 (*t*-statistic = 4.33). In economic terms, the results in column [1] suggest that a value-weighted portfolio with the least amount of price clustering generates a return premium of nearly 5.64%. As seen

**Table 9.** Portfolio analysis – five-factor regression analysis.

| | Q1 (Low) [1] | Q2 [2] | Q3 [3] | Q4 [4] | Q5 (High) [5] | Q5 – Q1 [6] |
|---|---|---|---|---|---|---|
| *Panel A. 5-Factor Regressions by Equal-Weighted Cluster% Portfolios* | | | | | | |
| ALPHA | 0.0023*** | −0.0006** | −0.0008** | −0.0006 | −0.0002 | −0.0026* |
| | (2.62) | (−2.17) | (−2.08) | (−1.40) | (−0.43) | (−1.93) |
| MRP | 1.1057*** | 1.0437*** | 1.0143*** | 0.9737*** | 0.8536*** | −0.2520*** |
| | (43.30) | (143.34) | (116.11) | (91.55) | (58.08) | (−6.65) |
| SMB | 0.0436 | −0.0323** | −0.0334** | −0.0138 | 0.0350 | −0.0085 |
| | (1.00) | (−2.02) | (−2.34) | (−0.69) | (1.29) | (−0.13) |
| HML | −0.0065 | −0.0028 | 0.0053 | 0.0007 | 0.0139 | 0.0204 |
| | (−0.17) | (−0.23) | (0.31) | (0.04) | (0.54) | (0.34) |
| UMD | −0.0980*** | −0.0459*** | 0.0054 | 0.0416** | 0.0969*** | 0.1949*** |
| | (−2.71) | (−6.00) | (0.43) | (2.09) | (5.02) | (3.63) |
| LIQ | −0.0176 | −0.0018 | −0.0035 | 0.0001 | 0.0192 | 0.0358 |
| | (−1.15) | (−0.33) | (−0.50) | (0.02) | (1.49) | (1.43) |
| *Panel B. 5-Factor Regressions by Value-Weighted Cluster% Portfolios* | | | | | | |
| ALPHA | 0.0050*** | 0.0004 | −0.0010** | −0.0006 | 0.0008 | −0.0042*** |
| | (4.50) | (0.71) | (−2.08) | (−1.15) | (0.94) | (−2.88) |
| MRP | 0.9623*** | 0.9758*** | 0.9998*** | 1.0343*** | 1.0340*** | 0.0717* |
| | (31.80) | (77.23) | (70.06) | (67.26) | (43.82) | (1.70) |
| SMB | 0.1057* | −0.0002 | −0.0160 | −0.0427* | 0.1653*** | 0.0596 |
| | (1.91) | (−0.01) | (−0.97) | (−1.88) | (4.42) | (0.78) |
| HML | 0.0033 | 0.0159 | 0.0604*** | −0.0091 | −0.0599 | −0.0632 |
| | (0.09) | (0.76) | (3.50) | (−0.47) | (−1.39) | (−0.97) |
| UMD | −0.1077*** | −0.0249 | 0.0025 | 0.0566*** | 0.0616** | 0.1692*** |
| | (−3.39) | (−1.31) | (0.19) | (3.75) | (2.25) | (3.41) |
| LIQ | 0.0298 | −0.0009 | −0.0027 | −0.0072 | −0.0133 | −0.0431 |
| | (1.55) | (−0.07) | (−0.31) | (−0.78) | (−0.75) | (−1.61) |

The table reports alphas from estimating the following equation using 479 months of data by portfolios based on Cluster%, which is the percent of days during the month that the prices for a particular stock close on round increments of $0.25 during the pre-decimalization period and $0.05 during the post-decimalization period:

$$R_t - R(f,t) = \alpha + \beta_1 \quad 〖MRP〗\ _t + \beta_2 \quad 〖HML〗\ _t + \beta_3 \quad 〖SMB〗\ _t + \beta_4 \quad 〖UMD〗\ _t + \beta_5 \quad 〖LIQ〗\ _t + \varepsilon_t,$$

where the dependent variable is the excess return of the portfolio over the 1-month T-Bill yield. The independent variables include the following variables. MRP is the market risk premium or the return of the market less the risk-free rate. SMB is the small-minus-big risk factor. HML is the high-minus-low risk factor. UMD is the up-minus-down momentum risk factor. LIQ is the Pastor-Stambaugh aggregate liquidity innovations factor. While the variables are measured over month $t$, the portfolios are sorted at the end of month $t-1$. Robust (White (1980)) $t$-statistics are reported in parentheses. Panel A consists of equal-weighted portfolios sorted in month $t-1$. Panel B consists of portfolios that are value-weighted sorted in month $t-1$. Column [6] reports the difference between extreme portfolios. *, **, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

in the remainder of the columns, estimated alphas are generally decreasing across increasing portfolios. Again, column [6] reports an estimated alpha using return differences between extreme portfolios of 0.0041 ($t$-statistic= −2.87). In annual terms, this alpha suggests a return premium of 4.92%. The findings in Table 8 support the notion that price clustering carries with it a negative return premium that is both economically and statistically significant and robust to both equal-weighted and value-weighted portfolios.

As additional robustness, we re-estimate Equation 3 but include the Pastor and Stambaugh (2003) liquidity risk factor. We note that the liquidity factors are only available until 2017. So, instead of analyzing 479 months (from February 1980 to December 2019), we are only able to include 455 months (from February 1980 to December 2017). Table 9 reports the results from this analysis. As seen in Panel A, when we evaluate equal-weighted portfolios, alphas are generally decreasing. Column [6] shows the results from using return differences between extreme portfolios. We find that the estimated alpha is −0.26%, which is statistically significant ($t$-statistic= −1.93). Panel B reports the results using value-weighted portfolio returns, and we again find that alphas are markedly higher in quintile 1 than in quintile 5. The high-minus-low difference (in column [6]) is − −1.93). Panel B reportsice clustering is associated with a reliable, negative return premium. These findings support our main hypothesis and suggest that in the cross-sectional of stocks, preferences (or demand) for round prices generate price premiums and subsequent negative returns.

## Price clustering and asset prices – demand-induced premium

In this final subsection, we assess whether the negative return premium associated with price clustering is in fact demand-driven. To do so, we rely upon the published work of Box and Griffith (2016) and Kim (2014) who show that price clustering is a function of

**Table 10.** Fama and MacBeth (1973) regressions – price clustering and expected returns by momentum.

| | Losers [1] | Winners [2] |
|---|---|---|
| Cluster% | −0.0203*** | 0.0011 |
| | (−4.86) | (0.42) |
| Beta | −0.0008 | 0.0006 |
| | (−1.46) | (0.87) |
| Capitalization | −0.0029*** | −0.0012*** |
| | (−5.07) | (−2.77) |
| B/M | 0.0098*** | 0.0070*** |
| | (12.32) | (10.27) |
| Momentum | −0.0088** | 0.0036*** |
| | (−2.52) | (2.85) |
| Illiquidity | 0.0001*** | 0.0002 |
| | (3.75) | (1.46) |
| Idiovolt | −0.0557 | −0.1339*** |
| | (−1.57) | (−3.34) |
| Constant | 0.0645*** | 0.0427*** |
| | (5.39) | (4.44) |

The table reports the Fama and MacBeth (1973) regression results from estimating the following equation using pooled stock-month data separated in extreme momentum quintiles (i.e. quintile 1 = losers; quintile 5 = winners):

$$R(i,t) = \beta_1 \; 〚Cluster\%〛_{(}\mathrm{i,t-1}) + \beta_2 \; 〚Beta〛_{(}\mathrm{i,t-1}) + \beta_3 \; \mathrm{Ln}(\; 〚Capitalization〛_{(}\mathrm{i,t-1})) + \beta_4 \; \mathrm{Ln}(\; 〚\mathrm{B/M}〛_{(}\mathrm{i,t-1})) \; + \beta_5 \; 〚Momentum〛_{(}\mathrm{i},\{\mathrm{t-12,t-2}\}) + \beta_6 \; 〚Illiquidity〛_{(}\mathrm{i,t-1}) + \beta_7 \; 〚Idiovolt〛_{(}\mathrm{i,t-1}) + \alpha + \varepsilon_{(}\mathrm{i,t}),$$

where the dependent variable is the return for stock *i* in month *t*. The independent variable of interest is Cluster%, which is the percent of days during the month that the prices for a particular stock close on round increments of \$0.25 during the pre-decimalization period and \$0.05 during the post-decimalization period. Beta is calculated as the slope coefficient from a daily CAPM. Capitalization the market capitalization on the last day of each month (in \$billions). B/M is the book-to-market ratio. Momentum is the return from month $t-12$ to $t-2$. Illiquidity is the Amihud (2002) illiquidity measure, which is the monthly average of the ratio of the absolute value of the daily return scaled by the daily volume. IdioVolt is the idiosyncratic volatility. To obtain this measure of volatility, we first estimate a daily four-factor model (Fama and French 1996; Carhart 1997) and obtain daily residual returns. We then calculate IdioVolt as the standard deviation of these daily residual returns. In parentheses, we report *t*-statistics that are obtained from standard errors with the Newey and West (1987) adjustments that include three lags. ** and *** denote statistical significance at the 0.05 and 0.01 levels, respectively.

order submission strategies and price movements. More specifically, Box and Griffith (2016) provide empirical evidence that as prices are rising, sell orders cluster more frequently on round increments than buy orders. In contrast, when prices are falling, buy orders cluster more frequently on round increments than sell orders. This assumes that limit order traders strategically place stop orders to either realize capital gains or mitigate capital losses. Because the future value of the asset is unknown, these traders are more likely to place such stop orders on round increments. In the context of our study, we argue that when stock prices are falling, pockets of clustered limit buy orders will artificially inflate the security price, which will result in subsequent price reversals.

Since our data do not allow us to observe the actual limit order submissions, we partition the data into monthly quintiles by *Momentum* to identify stocks that recently experienced price run-ups versus those that experienced price draw-downs. To the extent that the negative price clustering premium is related to demand, we would expect the results to be isolated to those securities that recently experienced losses as they will have to blow through more buy clustered limit orders (Box and Griffith 2016). Therefore, we re-estimate Equation 2 separately for the highest (winners) and lowest (losers) *Momentum* quintiles. For brevity, we only report the specifications when *Cluster*% is the independent variable of interest. The results of this analysis are found in Table 10. We find that the negative return premium associated with price clustering is entirely driven by recent losers or those that experienced recent price declines. The coefficient on *Cluster*% in column [1], where the sample is previous losers, is −0.0203, which is significant at the 0.01 level. This result indicates that a one percent increase in *Cluster*% is associated with a 203-bp decrease in next-month's return. The coefficient on *Cluster*% in column [2], where the sample is previous winners, is positive but not reliably different from zero. We believe that these results provide strong support for the assertion that the negative price clustering premium observed above is, in part, demand-driven.

## Conclusion

In this paper, we develop and test the hypothesis that price clustering influences asset prices. Prior research suggests that investors, and individuals generally, have strong preferences for round pricing increments. We contend that these preferences may produce demand-induced price premiums, which result in subsequent underperformance. This is predicated on the notion that clustered prices represent a less precise estimate of an asset's fundamental value, which has been documented in the previous literature (see e.g. Harris 1991; Ball, Torous, and Tschoegl 1985). To the extent that buy-side transactions on clustered values temporarily inflate asset prices, we might expect to find subsequent price reversals.

In a variety of cross-sectional and portfolio tests, we find evidence supporting this idea. In a series of Fama and MacBeth (1973) regressions, we find that, after controlling for several stock characteristics that have been shown to influence future stock returns, price clustering meaningfully predicts negative next-month returns. In fact, in these cross-sectional tests, we find that the negative return premium associated with price clustering ranges from 64 to 85 bps per month. We find that these results are robust to changes in the functional form of our measure of price clustering, to controls for both the pre-decimalization and the post-decimalization periods, and to transaction-level data.

Next, we estimate a series of multi-factor models for portfolios sorted by the level of price clustering. In general, we find that next-month returns, and alphas, are decreasing across increasing portfolios. Stocks with the lowest levels of price clustering exhibit significant alphas and the difference between extreme portfolios range from about 25 bps per month to approximately 42 bps per month, depending on the factor model. In annual terms, these results indicate that a long-short strategy based on price clustering results in a negative return premium from about 3% to 5%. Combined with the cross-sectional tests, these findings indicate that the anomalous presence of price clustering, which has been well documented in the literature, leads to negative expected returns.

## Notes

1. See e.g., Niederhoffer (1965, 1966), Niederhoffer and Osborne (1966), Harris (1991), Christie and Shultz (1994), Christie, Harris, and Schultz (1994), Gwilym, Clare, and Thomas (1998a, 1998b), Sopranzetti and Datar (2002), Gwilym and Alibo (2003), Ni, Pearson, and Poteshman (2005), and Sonnemans (2006), among others.
2. Clustering has been shown to exist in commodity markets (Ball, Torous, and Tschoegl 1985), bond markets (Gwilym, Clare, and Thomas 1998a), money markets (Sopranzetti and Datar 2002), and derivative markets (Gwilym, Clare, Thomas 1998b; Gwilym and Alibo 2003; Ni, Pearson, and Poteshman 2005).
3. Admittedly, other researchers have examined how price clustering might affect trading strategies. For instance, Bhattacharya, Holden, and Jacobsen (2012) acknowledge the presence of price clustering on round prices (or pricing increments of $0.05) and examine a trading strategy where the investor buys at prices on integers one penny below round increments and sell at prices on integers on one penny above round pricing increments. Intraday trading strategies at the 24-hour interval yield mixed results regarding the profitability of these strategies.
4. In unreported Fama and MacBeth (1973) cross-sectional tests, we find that price clustering leads to higher future stock prices. These results support the notion that the demand for round numbers places upward pressure ("pushes up") on stock prices.
5. For the TAQ sample, we remove stocks with average intraday prices of less than $1 due to inactive trading, which creates inconsistencies in the clustering measures.

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